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Simulated CSM-CROPGRO-cotton yield under projected future climate by SimCLIM for southern Punjab, Pakistan

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ABSTRACT

Climate change is widely affecting the agriculture sector in Pakistan with an estimated annual loss of up to 16 billion dollars by the end of 21st century (GOP, 2015). Southern Punjab is famous for producing more cotton than the entire province of Sindh in Pakistan but here the climatic variations largely affect the cotton production. The present research was carried out in Vehari, an arid area of Southern Punjab, Pakistan, to determine the intensity of the climatic impacts on the projected agricultural production of cotton in southern Punjab for 2025 and 2050 using SimCLIM(climate model) with CSM (crop simulation model)-CROPGRO-Cotton by comparing with observed data (2013 and 2014).The integrated assessment model (IAM) SimCLIM uses a statistical approach for regional downscaling. Scenarios for two general circulation models (GCMs) (BCC-CSM1–1 and MIROC5) and three greenhouse gas concentration pathways (RCP-8.5, 6.0, 4.5) were developed. The three levels of phosphorous (0, 57, and 114 kg ha^{-1}) were applied to find the yield output of cotton cultivars (MNH-886 and FH-142) for the prediction of development and yield with different GCMs. The model predicted that FH-142 would give a higher percentage yield than MNH-886 for 2025 and 2050; the lowest percentage yield would be for MNH-886 at maturity for three RCPs. The lowest percentage change in the yield was projected for MNH-886 by RCP-8.5 (− 0.77) and (− 0.85) for 2025 and 2050, respectively. Farmers might have to apply a moderate level of phosphorous (57 kg P ha^{-1})to avoid the potential threat of climate change. Both the cultivars MNH-886 and FH-142 are suitable for 57 kg P ha^{-1}, but cultivar FH-142 performed better when compared to MNH-886 for GCM and three RCPs.

1. Introduction

Cotton is a major cash and fiber crop in Punjab, Pakistan, in terms of production and acreage (GOP, 2015). Several studies found that the world's climate is changing and multiplying the natural disaster risks (FAO, 2015; Amanullah et al., 2017; Fahad et al., 2013, 2014a,b, 2015a,b), and agriculture is at risk due to imminent climate change (Nasim et al., 2016b; IPCC, 2014; Zahid et al., 2014; Nasim et al., 2011; Sakurai et al., 2011; Fahad et al., 2016a,b,c,d). Multiple studies have been carried out to investigate the impact of climate variations on

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cotton production, including in Punjab where agriculture is a main economic support (Ishaq and Memon, 2016; Wajid et al., 2014). To manage the climate risks different tools have been developed to estimate future agricultural yields (Amin et al., 2017a, b; Nasim et al., 2012). Climate variations are projected based on climate models (Challinor et al., 2014), and these models are extensively used all over the world (Rosenzweig et al., 2013). Different approaches and a variety of parameters have been tested to develop the basic structure to influence crop development and growth (Khan et al., 2016; He et al., 2013; Mubeen et al., 2013; Pirttioja et al., 2015; Asseng et al., 2015; Mubeen et al., 2016). These model tools also work for crop responses and predictions under climatic stresses such as drought, nutrient limitation, pests and diseases, waterlogging, high temperature variations, changing atmospheric CO_2 concentrations, and precipitation. With the support of the Intergovernmental Panel on Climate Change (IPCC), various crop models have been developed to investigate the impact of possible climate change on crop yield in different region, scenarios and assumptions (Nasim et al., 2017; Ali et al., 2016; Anjum et al., 2016; Field et al., 2014; Boot-Handford et al., 2014).Future climate predictions were studied using joint projections of general circulation models (GCMs) with the cropping system model CSM-CROPGRO model (Adhikaria et al., 2016; Nasim et al., 2016a; Qasim et al., 2016; Bao et al., 2015a). This specific approach was effective for the evolution of models and the study of combined effects of climate variations on crop growth and yield. Climate models developed by the Goddard Institute for Space Studies (GISS), Geophysical Fluid Dynamics Laboratory (GFDL), and the United Kingdom Meteorological Office (UKMO) used to enhance the research about the environmental interaction in future climate change (Bao et al., 2015a). The Commonwealth Scientific and Industrial Research Organization (CSIRO) model, a GCM, and RCM-RegCM2 were used for future agricultural yield projections in different climatic scenarios (Mearns et al., 2003). The performance of two GCMs models (BCC-CSM-1, and MIROC5) in simulation of climate change for the South Asian region was acceptable out of other 40 GCMs models. GCMs have been used successfully by other researchers with other crops in Punjab. Climate change conditions were captured well by the two models BCC-CSM-1 and MIROC5 in south Asia recommended by Zahid et al. (2014) used in this study.

Various studies have shown the potential threats of climate change on crop production and researchers must address the potential challenges. A newly developed data set covers the wide range of values for the presentation of future greenhouse gas emissions. These data sets, ranging from economic to demographic and technological developments, are managed by Special Report on Emissions Scenarios (SRES)·Studies have shown that the crop model simulation for selected location can represent the entire grid(Bao et al., 2015a). However, a study by Christensen et al. (2007) found that GCM is not suitable for regional scale projections. While Mearns et al. (2003) showed that RCM at 50 × 50 km is more suitable, Tsvetsinskaya et al. (2003) used CSIRO and RegCM2. It is important to develop a climate projection model for a specific location that fulfills the local input crop simulation model requirement.

The main purpose of this study was to access ability of the SimCLIM (an integrated assessment model) for the projections of temperature and precipitation by GCMs to demonstrate the importance of climate adaptation in the study area. The CSM-CROPGRO was used to investigate the simulation of crop yield by collaboration with GCM climate projections. The study's particular objectives, for the two crop cultivars at this site, were(1) to examine multi-model responses of percentage change in precipitation and temperature variability and reliability,(2) to calculate percentage change in yield responses to projected climate for the period of 2025to 2050 in southern Punjab, Pakistan, and(3) this research was to develop some projection of climate change effects on cotton growth and yield for the specific district of Vehari in Southern Punjab, Pakistan.

Table 1
Two cotton genotypes for different yield variables with P application (57 kg P ha^{-1}) and validation.

Variables	Cultivars	Observed	Simulated	%Error	RMSE
Anthesis (day)	MNH-886	66	66	0	0
	FH-142	70	70	0	0
Maturity (day)	MNH-886	163	163	0	0
	FH-142	170	170	0	0
Seed cotton yield (Mg ha^{-1})	MNH-886	2.23	2.13	− 4.40	0.09
	FH-142	2.45	2.55	4.00	0.09
Total dry matter (Mg ha^{-1})	MNH-886	7.62	8.57	12	0.95
	FH-142	7.71	9.18	19	1.47
Harvest index (%)	MNH-886	0.22	0.25	13	0.03
	FH-142	0.24	0.28	16	0.04

2. Methodology

2.1. Site selection and crop management practices

Vehari, an arid area of southern Punjab, Pakistan, (30.01°N, 72.31°W) was selected as a case study. Southern Punjab (especially Vehari) is famous for producing more cotton than the province of Sindh (Pakistan) but here the climatic variations largely affect the cotton production. The two cultivars (MNH-886, FH-142) were selected with the recommendations of the Adaptive Research Farm, Vehari due to its better yield reported by Amin et al. (2017a) in the region. Data of growth, and yield for the two cultivars were validated with phosphorous levels (57 kg ha^{-1}) (Table 1) detail is given in Amin et al. (2017a) for other phosphorous levels. Recommended farming techniques were practiced for the crop management. For further detail about base data and standard crop management practices described by Amin et al. (2017a) were followed.

2.2. Climate models

An integrated assessment model, SimCLIM was developed by CLIMsystems, Flagstaff, Hamilton, NewZealand, for the assessment of climate variations and their effects on different areas of the world (Warrick et al., 2005; Kenny et al., 2000). Different potential risks of climate on crop production (Jamieson and Cloughley, 2001; Bao et al., 2015b), regional resources (Kenny et al., 2001a), soil and land systems (Parshotam and Tate, 2001), pasture management (Clark et al., 2001),and sea level rise (Warrick et al., 2005) were studied for NewZealand. Projections of temperature and precipitation (data set) are available for Pakistan. SimCLIM was also used for the CSM-CROPGRO-Soybean model to predict the effect of climate change on soybean yield in 2025 and 2050 for Tifton, Georgia, USA (Bao et al., 2015a). The CMIP5 was used for assessment of soil moisture changes over South Asia (Zahid et al., 2014). SimCLIM can be joined with different impact models for crop assessment and pasture productions (Warrick, 2009). SimCLIM has also been used with numerous crop models for horticultural and arable crops, as well as for pasture management (Warrick et al., 2001; Warrick, 2009).

SimCLIM used 40 GCMs from local, regional, national, and site specific levels for different countries of the world, including Pakistan (Amin et al., 2017a). IPCC generated patterns followed by SimCLIM main emphasis of SimCLIM 2013 being the selection of datasets (IPCC CMIP5) and use of baseline data (ranging from 1986 to 2005) which centered on 1995 (Yin et al., 2013). The SimCLIM 2013 used a bilinear interpolation method to deal with the basic spatial scale dataset from their original resolution to 0.5° × 0.5° degrees for baseline and future projections (Yin et al., 2013). The climatic predictions from 1991 to 2100 for different datasets of the world can be generated by using SimCLIM 2013. According to the IPCC in its Fifth Assessment Report (AR5), there are four Representative Concentration Pathways (RCP-2.6, 4.5, 6.0, and 8.5) known as gas concentration scenarios with the values

2.6, 4.5, 6.0, and 8.5 Wm^{-2} respectively for future projections up to 2100. SimCLIM was developed to find out the effects of climate change on crop production and climatic risks (Kenny et al., 2001b). This allow for comparing the spatial and temporal scales for different GCMs output and input required for impact assessments. SimCLIM has been used to study climatic variations for various fields like agriculture (Kenny et al., 2001b; Bao et al., 2015a), water supply (Warrick, 2007), coastal zones (Abuodha, 2009), and ecosystems (Storey, 2009).

2.3. Climate model selection

In order to study the impact of the future climate predictions for local or regional scale, the suitable GCMs should be used (Pierce et al., 2009; Bao et al., 2015a).For a wide-range study more than one GCM pattern should be selected because the use of one GCM has been shown to limit the projections (Hulme et al., 2000). In order for accurate predictions of future climate, models are acceptable only if they can predict the current climate accurately (Coquard et al., 2004; Amin et al., 2016). Pierce et al. (2009) found that the selection of a GCM should consider its ability to predict local or regional climate.

Future climate change is subject to considerable uncertainty. One important aspect in climate change vulnerability and adaptation (V & A) assessment is to comprehend the range uncertainty in decision making and policy planning processes. Within this context, any climate change scenario constructed on single Greenhouse Gas (GHG) emission rate and/or individual GCM output is generally considered inappropriate for V & A assessment purposes, because it cannot provide information of the uncertainty range associated with its projection. In this study, to address the uncertainties in future GHG emission rates and in climate sensitivity, a combination of different GHG RCPs and climate sensitivities were used to differentiate the future climate change scenarios with the possible error range. RCP-6.0 represents mid-climate projection sensitivity with a middle range future global change scenario, that was used as an indicator of the median projection for future climate change, while RCP-4.5 with low-climate sensitivity and RCP-8.5 with high-climate sensitivity were used as indicator of the corresponding low and high level of uncertainty range, respectively. Another important uncertainty in climate change scenario generation is the variability in different GCM simulations. To account for such uncertainty average of two GCMs for climate variable is normally used to capture the middle values, as that average often matches better with observed climate than any individual model estimates (Reichler and Kim, 2008). However, in this study the two GCM models (used for Pakistan) were applied to mitigate the variations of large outliers in some GCM projections on the final change values.

To study the region's based projections, two climate models (BCC-CSM1–1, and MIROC5) were selected from SimCLIM. Selected GCM can predict the current climate trends accurately, so their future projection for temperature and precipitation are accepted (Zahid et al., 2014). These GCM predict current climate accurately and used for the future projections (2025, 2050). The daily observed rainfall and temperature data from 1980 to 2011 were used as baseline data. Besides the spatial monthly change projections, site specific climate change scenarios with more detailed time scale are usually needed for risk assessment. The site specific climate change scenarios were assembled by using daily observed weather data of specific station with normalized GCM pattern value from the GCM grid, where the climate station was located (Amin et al., 2017b).

Based on analysis of observational data, the IPCC (2007) has shown that there is evidence of increasing temperatures across the globe. The analysis of 31 years of data (1980–2011)for Southern Punjab, Pakistan, also showed increasing trends to support this IPCC statement as, in general terms, the local data indicate that annual mean temperatures have been increasing across the country accessed from National Aeronautics and Space Administration (NASA) (http://power.larc.nasa.gov) as shown in Fig. 1. The IPCC (2007) has also indicated that

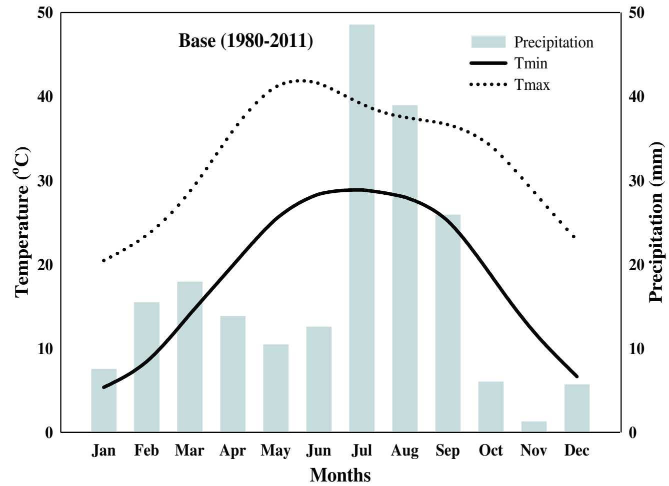

Fig. 1. Historical trend of precipitation, maximum, and minimum temperature for the Southern Punjab (Pakistan) for the base years (1980–2011).

temperatures will continue to shift in accordance with increasing atmospheric concentrations of greenhouse gas emissions. Fewer cold days and more hot days are expected, with associated shifts in annual and seasonal means and extremes.

2.4. Cotton yield prediction with the CSM-CROPGRO-cotton model

The CSM-CROPGRO-Cotton model simulates the soil and plant carbon, water, phosphorous, and nitrogen balances for cotton based on crop genetics, including cultivar precise parameters or cultivar coefficients(Jones et al., 2003; Thorp et al., 2014), and is one of the crop models included in the Decision Support System for Agro-technology Transfer (DSSAT) (Hoogenboom et al., 2015; Nasim et al., 2016c). The CSM-CROPGRO-Cotton model has been evaluated widely for yield predictions and finding out the response to genetic behavior and various management practices in the Southern Punjab (Wajidet al., 2014). DSSAT Version 4.6.1 (Hoogenboom et al., 2015) was developed to simulate growth and yield under various conditions for 31 crops. Minimum inputs required for the crop model operations are weather data, crop management data, soil data, and initial conditions (Hoogenboom et al., 2012).

For early cotton growth and development, initial conditions are of vital importance. These conditions were defined using wheat: initial crop residue was 4000 kg $ha^{-1}$with the nitrogen concentration 3% present at the depth of 15 cm and wheat root residue was 200 kg ha^{-1}.The soil profile used for the current experiment was Jaranwala (silt loam) suitable for current soil situations. In the crop management the plant population was set 3 plants m^{-2} at seeding and plant emergence, plant depth was kept at 4 cm and row to row distance was 75 cm. For irrigation management, 15irrigationswere applied from seeding to crop harvest. Genetic coefficients were calculated for crop simulation given in Table 2. The Weather Man program of DSSAT was executed with daily maximum, minimum temperature and precipitation. Long term historical weather data for 31 years (1980–2011) were obtained from the Multan station in Southern Punjab. Projected Climate data were provided by the SimCLIM used in crop model for dynamic crop simulation. For further detail about model calibration see Amin et al. (2017a, b).

3. Results

3.1. SimCLIM projections for 2025 and 2050

The projections for monthly precipitation (Fig. 2)and mean temperature (Fig. 3)for 2025 and 2050 were generated with SimCLIM base

Table 2
Genetic coefficients for two cotton (MNH-886, FH-142) cultivars for calibration of CSM-CROPGRO-Cotton.

ECO#	VRNAME	CS DL 1	PPS EN 2	EM -FL 3	FL -SH 4	FL -SD 5	SD -PM 6	FL -LF 7	LF MAX 8	SL AVR 9	SI ZLF 10	XF RT 11	WT PSD 12	SF DUR 13	SD PDV 14	PO DUR 15	THR SH 16	SD PRO 17	SD LIP 18
CO0001	MNH-886	23	0.01	51.5	13.5	18	55	117.8	0.75	185	180	1.3	0.18	27.5	27	2.9	79	0.153	0.12
CO0003	FH-142	23	0.01	54.2	14	20	55	117.8	0.74	185	180	1.3	0.18	27.5	27	2.9	79	0.153	0.12

ECO# = Ecotype code to which this cultivar belongs
CSDL = Critical Short Day Length under which reproductive growth progress with no day duration cause (for short day plants) (hour)
PPSEN = Slope of the comparative reaction of growth to photoperiod by (positive for shortday plants) (1/h)
EM-FL = Time among plant appearance and flower emergence (R1) (photothermal days)
FL-SH = Time among first flower and first pod (R3) (photothermal days)
FL-SD = Time among first flower and first seed (R5) (photothermal days)
SD-PM = Time among first seed (R5) and physiological maturity (R7) (photothermal days)
FL-LF = Time among first flower (R1) and end of leaf extension (photothermal days)
LFMAX = Greatest leaf photosynthesis speed at 30C, 350 vpm CO2
SLAVR = Precise leaf area of cultivar under average growth situation (cm2/g)
SIZLF = Maximum size of full leaf (three leaflets) (cm2)
XFRT = Maximum division of daily development that is partitioned to seed + shell
WTPSD = Maximum weight per seed (g)
SFDUR = Seed filling interval for pod cohort at standard growth situation (photothermal days)
SDPDV = Standard seed per pod under standard growing situation (#/pod)
PODUR = Time required for cultivar to reach final pod load under optimal conditions (photo thermal days)
THRSH = Threshing percentage. The maximum ratio of (seed/(seed + shell)) at maturity. Causes seeds to stop growing as their dry weight increases until the shells are filled in a cohort.
SDPRO = Fraction protein in seeds (g(protein)/g(seed))
SDLIP = Fraction oil in seeds (g(oil)/g(seed)).

on two GCMs, i.e. BCC-CSM-1 and MIROC5, and the three greenhouse gas concentration pathways, RCP-8.5, 6.0, and 4.5. The precipitation varied by year, month, and climatic scenarios for BCC-CSM-1 GCM model for both the 2025 and 2050 projections. The projected trends for the change in precipitation (based on BCC-CSM-1) for 2025were the same for the given months compared to that in the projection of 2050with a slight increasing trend. For example, BCC-CSM-1 projected a decrease in precipitation for January for 2025 and 2050, but a larger decrease was observed in 2050. Among the three RCPs, the projection for precipitation for 2025 based on the RCP-8.5 changed the most,

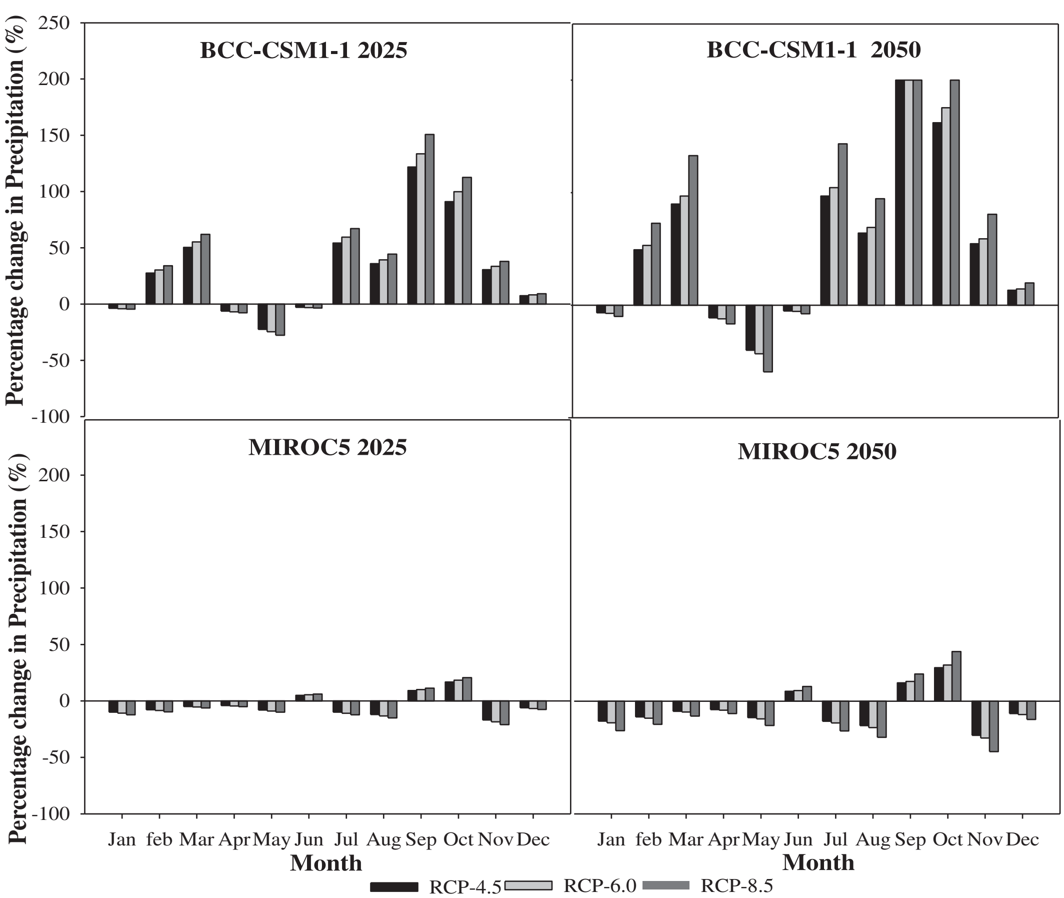

Fig. 2. Percentage change in monthly precipitation in the study area (Southern Punjab, Pakistan) projected for 2025 and 2050 by the global climate models BCC-CSM1–1 and MIROC5.

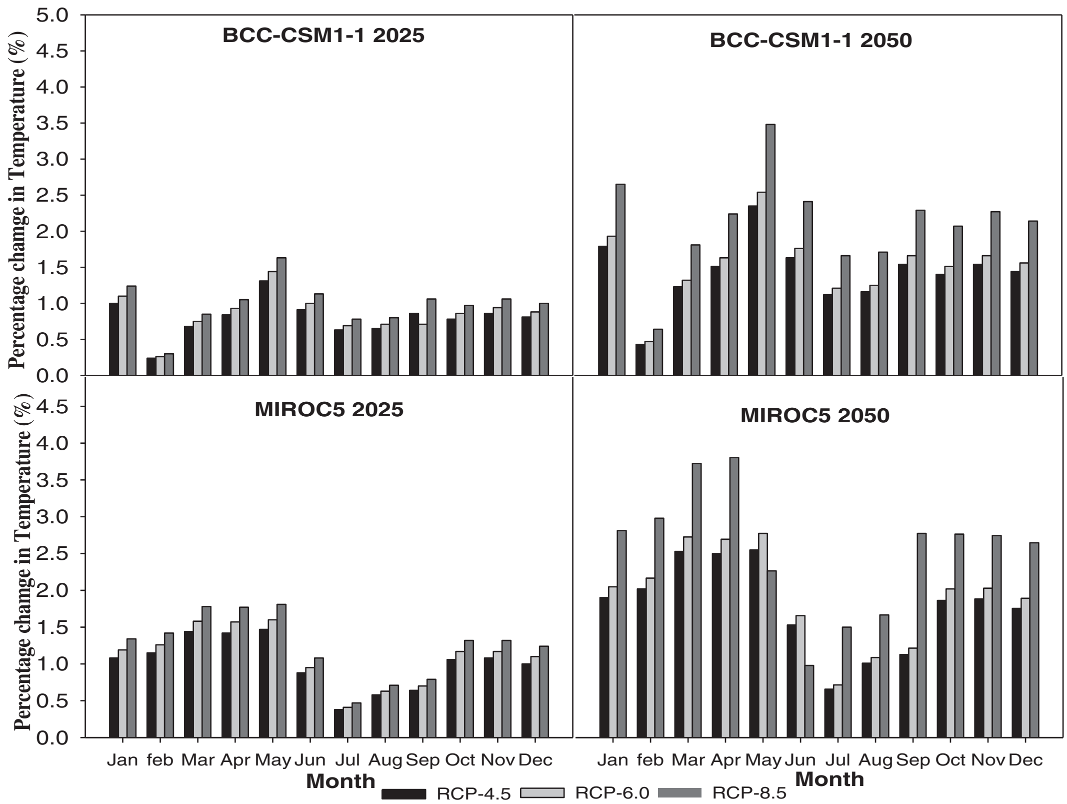

Fig. 3. Percentage change (%) in monthly mean temperature in the study area (Southern Punjab, Pakistan) projected for 2025 and 2050 by the global climate models BCC-CSM1–1 and MIROC5.

followed by RCP-6.0, and RCP-4.5. For 2050, the change in precipitation was the highest based on the RCP-8.5, followed by RCP-6.0and RCP-4.5. The differences among the three scenarios were larger for 2050 than 2025. The BCC-CSM-1 projections of precipitation for 2025 showed a decrease compared to the base line of − 4.5 to − 3.8% for January, − 7 to − 6% for April, and − 3 to 2% for June. By variations, precipitation for 2025 was projected to increase by 27 to 34% for February and 50 to 62% for March, and it started decreasing for April, May, and June; after these months precipitation percentage started to increase for July to September and then decreased steadily from October to December for 2025. The differences among RCPs were no more than 3% for 2025. The BCC-CSM-1 projections of changes in precipitation from the baseline for 2050 ranged from − 10 to − 6% for January, 132% for March, − 16% for April, 72% for February, and they increased for March but decreased for the next three months, and then increased 200% for September and October. The yearly differences between projections of 2025 and 2050 were 79%, and variations between the RCPs were approximately 23% and 21%for 2025 and 2050, respectively.

MIROC5 projections of changes in precipitation differed from those of BCC-CSM-1 (Fig.2). For MIROC5, projected changes for precipitation decreased by 12% and 26% and then increased by 5.14%for January to April and precipitation 6.14%, 13% for June and highest precipitation increase was in October, 20% to 44% for 2025 and 2050 respectively. The changes in precipitation for January, February, March, April, and May ranged from 16 to 35% for 2025 and were similar for 2050. The rate of changes for September, October, and June ranged from 6 to 20% for 2025 and from 13 to 44% for 2050. The differences among RCPs were approximately 8 to 19%for 2025 and 6 to 32% for 2050. Compared to BCC-CSM-1, the changes in precipitation based on MIROC5 were smaller (Fig. 2). The variations were observed in monthly mean temperature for 2025 and 2050 by month, year, GCM, and scenarios. However, the monthly mean temperature increased for all 12 months for both 2025 and 2050 projections (Fig.3). In general, the increase in monthly mean temperature was, as expected, greater for 2050 than for 2025. The increase in temperature based on MIROC5 projections was higher than BCC-CSM-1. The monthly mean temperature projection for both 2025 based on the RCP-8.5 increased the most, followed by RCP-6.0 andRCP-4.5. For 2050, the largest change in monthly mean temperature was based on RCP-8.5, followed by 6.0, and 4.5 RCPs, while the smallest change was found for the RCP-4.5. The differences among scenarios were larger for 2050 than for 2025. The increase in the monthly mean temperature ranged from 1 °C to 1.6 °C for 2025 and from 1 °C to 3.5 °C for 2050 based on BCC-CSM-1; from 0 °C to 1.8 °C for 2025 and from 0 °C to 3.9 °C for 2050 based on MIROC5. The differences among scenarios ranged from 0.1°Cto 0.3 °C for 2025 and 0.3 °C to 0.9 °C for 2050 inMIROC5, 0.1 °C for 2025 and 0.9 °C for 2050 in BCC-CSM-1.

3.2. Crop development projections

Average of both GCM (MIROC5 and BCC-CSM-1) climate projections were used for the prediction of cotton yield, growth, and development predictions by using CSM-CROPGRO-Cotton model. Rather than analyzing the absolute cotton yield predictions, our analysis was based on the differences between the cotton simulations for the reference years and those for 2025 and 2050 projections based on both climate patterns. In general, the number of days to anthesis for both cultivars increased and the number of days to maturity for all cultivars increased compared to the reference years because of the increase in temperature.

Anthesis days for both cultivars increased compared with the observed year. The change in anthesis day for both cultivars and different phosphorous levels are given in Fig. 4. For the year 2025 the anthesis day projections showed less variation compared to year 2050, which were slightly larger among the three RCPs. For 2025 projections

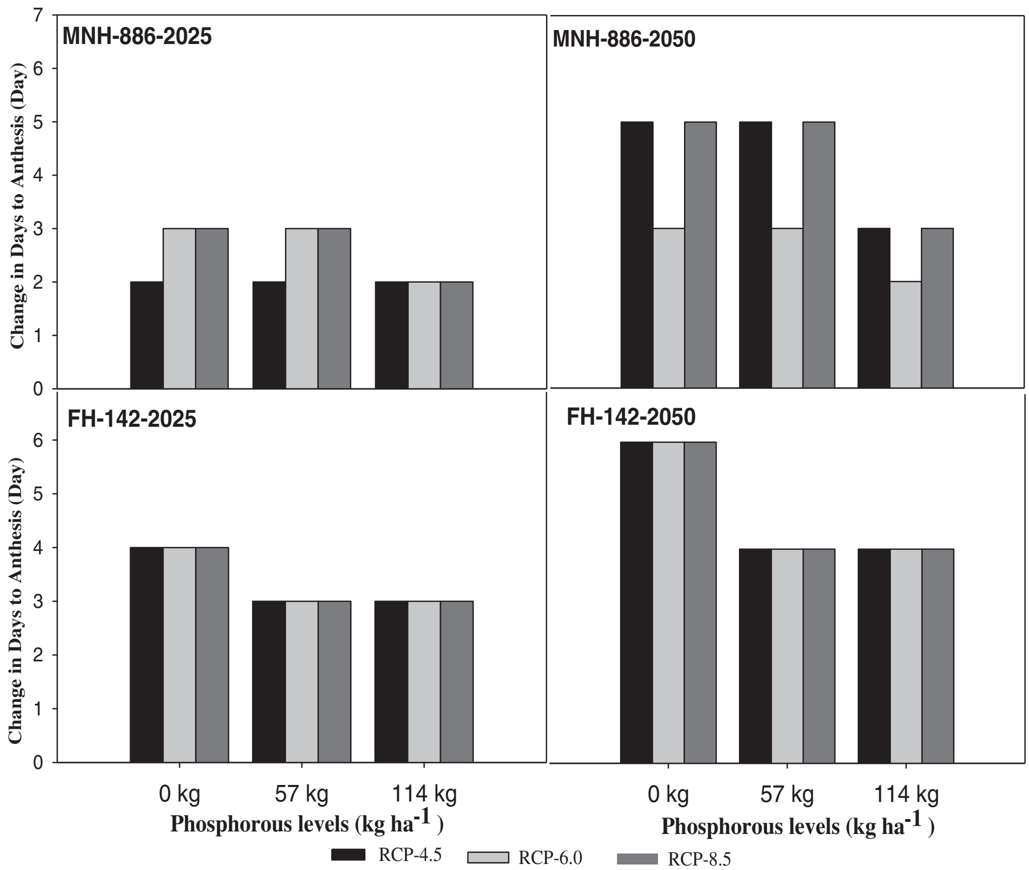

Fig. 4. Change in the number of days to Anthesis (days) for Cotton projected by the GCMsBCC-CSM1–1 and MIROC5 for 2025 and 2050.Values are shown for three RCPs, two cultivars and three phosphorous levels.

days to anthesis for MNH-886 changed 2 to 3 days for three RCPs and show same values for 0 kg P ha^{-1} and 57 kg P ha^{-1} but shows 0 to 2 days change in case of 114 kg P ha^{-1}. MNH-886 shows different behavior in projection of 2050 RCP-8.5 and 4.5 shows similar values but 6.0 predicted low values as compared to other 2 RCPs. FH-142 predicted the change of 3 to 5 days for 0 kg P ha^{-1} and 3 days change from the base for 57, 114 kg P ha^{-1}. Three RCPs demonstrated the 5 days in anthesis days for 0 kg P ha^{-1} but 3 days variations for prediction of 57, 114 kg P ha^{-1} in the year 2025. For 2050 the anthesis days shows variations greater than 2025 for both cultivars and phosphorous levels under three RCPs, FH-142 shows variations from 3 to 6 days for 0 kg P ha^{-1} and 1to 4 days change in anthesis days at the rate of 57,114 kg P ha^{-1}, both the cultivars show high variation in projections of 2050 as compared to 2025.

Change in the number of days to maturity varied by phosphorous levels, cultivar, GCM, scenario, and projection year. Based on the average of both GCMs, the increase in the number of days to maturity was larger for 57 kg P ha^{-1} compared to other phosphorous levels for both cotton cultivars (Fig.5). The higher the predicted increase in the monthly mean temperature among the three RCPs by two GCMs (Fig. 3), the larger the predicted increase in the number of days to maturity for the 2025 projections. As expected, the increase in the number of days to maturity and differences among the scenarios was larger for the 2050 projections than for the 2025 projections (Fig. 5). For the 2025 projections, the number of days to maturity for the cultivar MNH-886 increased by 2 days when applied 114 kg P ha^{-1} but only 1 day when applied 57 kg P ha^{-1}; the cultivars FH-142 showed a small change in days to maturity 3 days increase at 57 kg P ha^{-1} and maturity days decrease 2 days at 114 kg P ha^{-1}. However, the cultivar MNH-886 showed more increase in maturity of cotton in 2050 (6 days) as compared to 2050 for RCP-8.5. Among the 3 RCPs the greatest increase was observed for the RCP-8.5 followed by 6.0, while 4.5 showed similar changes for both cultivars with a difference among the three RCPs of 3 days. For the 2050 projections, cultivars FH-142 and MNH-886 showed little change in number of days to maturity when applied 114 kg P ha^{-1} and 0 kg P ha^{-1} respectively. The increase in the number of days to maturity for FH-142 cultivar did not show large differences among phosphorous levels: changes ranged from 2 days for 0 kg P ha^{-1}, and from 1 day for the 57 kg P ha^{-1} and for MNH-886 large difference was observed 2 to 3 days at 114 kg P ha^{-1}. The largest increase was found based on the RCP-8.5 and followed by 6.0 and 4.5 which had similar predictions.

3.3. Yield projections

The average of both GCMs showed slight increase in monthly mean temperature and also showed an increase in CO_2concentration that resulted in improved yield of both cultivars under different phosphorous levels (Fig.3). Generally, MNH-886 based on GCMs did not show very large differences among the different phosphorous levels and RCPs. The increase in yield was similar for the two cultivars, especially for the 2025 projections (Fig.6). Phosphorous level 57 kg ha^{-1} showed higher increases in yield, especially for cultivar FH-142. Among the three RCPs, the increase in yield based on the RCP-6.0 was higher followed by RCP-8.5 and 4.5. The increases in yield for the 2050 projections were larger than those for the 2025 projections because of the larger increases in precipitation and CO_2 concentration for the 2050 projections. For the 2025 projections, MNH-886 shows more variation in yield at maturity; it was projected at 5.4 to −0.7%, 3.8% and 1.7% for RCP-8.5, 6.0 and 4.5 respectively at the rate of 57 kg P ha^{-1},but at other phosphorous levels, it showed a greater difference as compared to 57 kg P ha^{-1}. For 2050, MNH-886 showed low yields for three RCPs

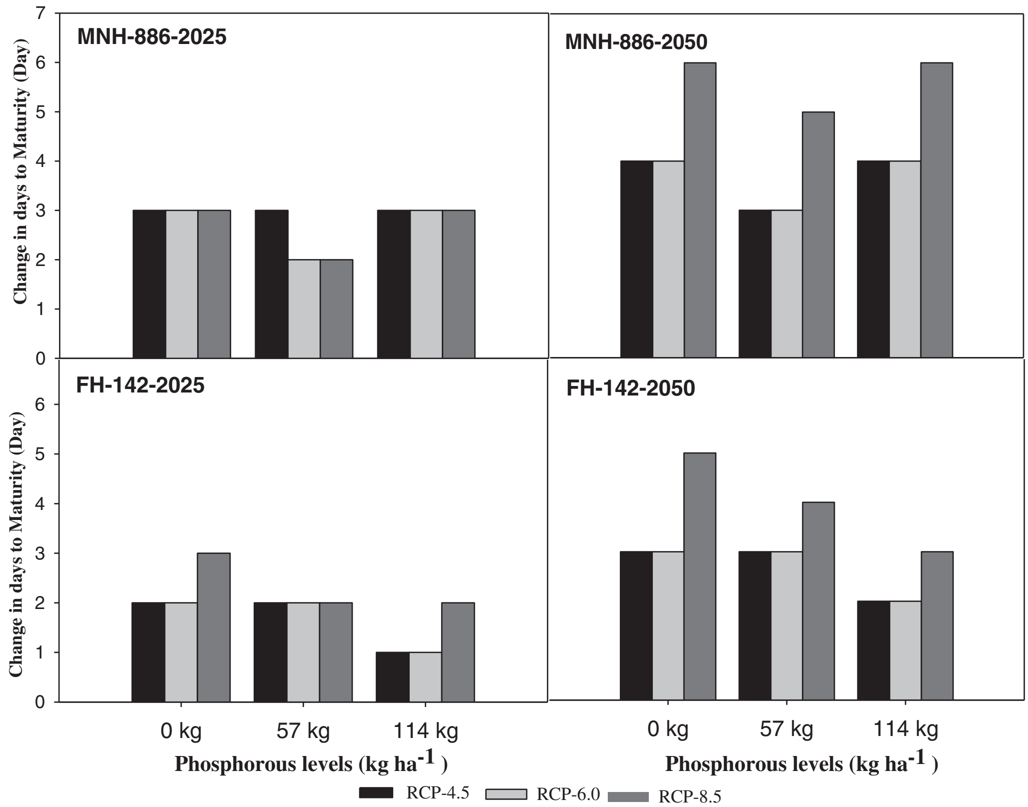

Fig. 5. Change in the Number of Day to maturity (Days) for Cotton projected by Average of GCMsBCC-CSM1–1 and MIROC5for 2025 and 2050. Values are shown for three RCPs, two cultivars and three phosphorous levels.

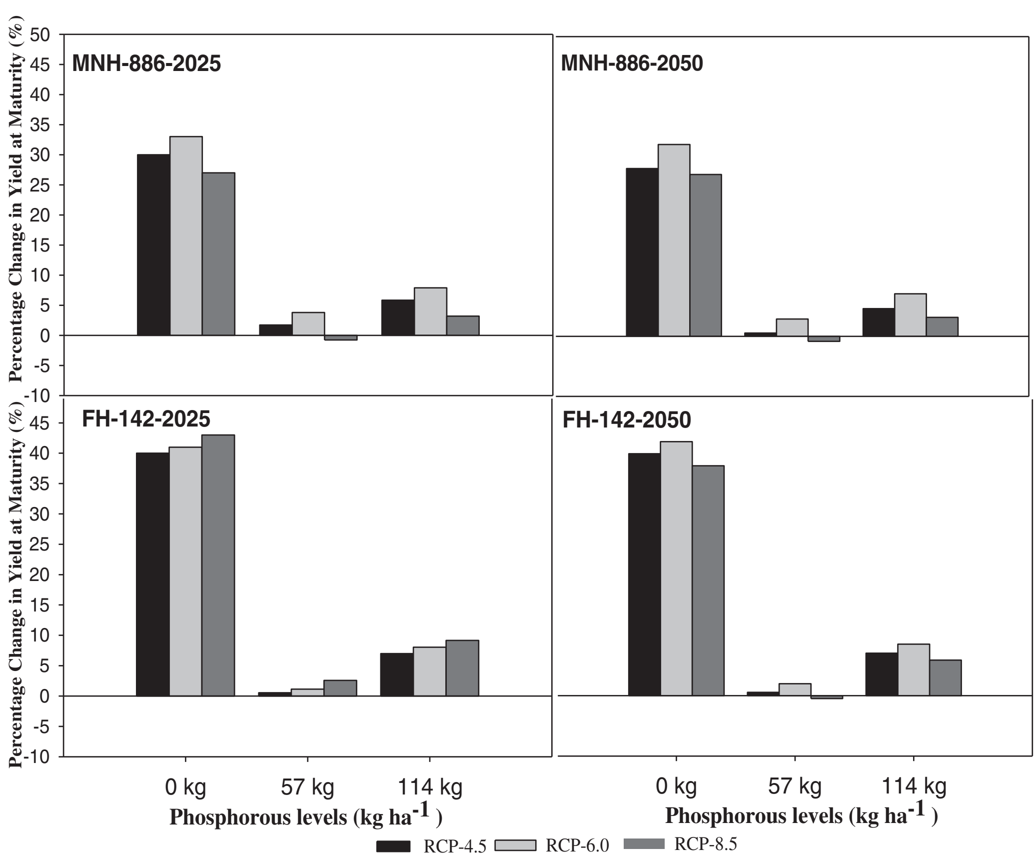

Fig. 6. Change in the Yield at harvest maturity (%) for Cotton projected by Average of GCMsBCC-CSM1–1 and MIROC5for 2025. Values are shown for three RCPs, two cultivars and three phosphorous levels.

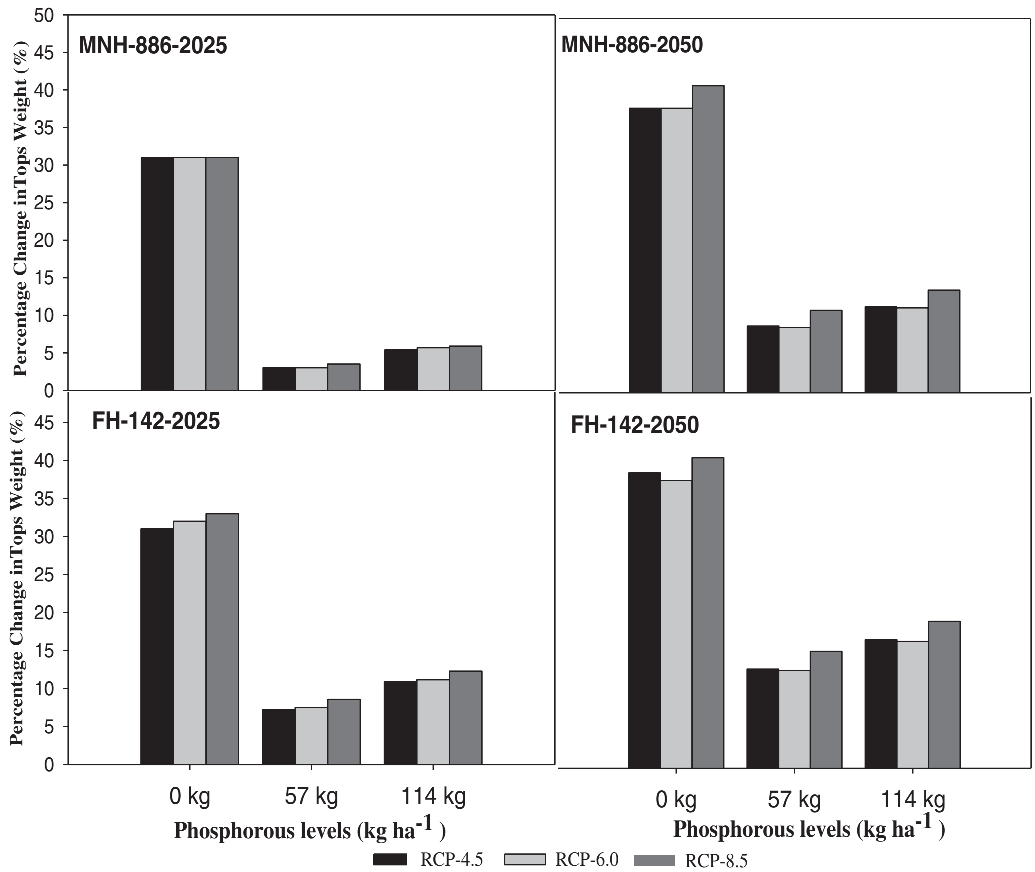

Fig. 7. Change in the Tops weight (%) for cotton projected by average ofGCMsBCC-CSM1–1 and MIROC5for 2025 and 2050. Values are shown for three RCPs, two cultivars and three phosphorous levels.

under all phosphorous levels due to higher temperature stress issue. FH-142 showed 3.3% change in yield at maturity compared to three scenarios; 2.3, 1.2, and 0.6% change were predicted by RCP-8.5, 6.0,and 4.5 respectively. Model predictions of 2050 for FH-142 showed a decrease in yield by all the scenarios compared to 2025.The increase in yield for both cultivars with phosphorous level 114 kg ha^{-1} was approximately 2.5 to 3.5% higher than for cotton 114 kg P ha^{-1}. For the year 2025, tops weight projection for both cultivars increased compared with the base line conditions. Variations in tops weight for different phosphorous levels are shown in Fig. 7. A similar trend was shown by the prediction of GCMs for the years 2025 and 2050. The change in tops weight under different phosphorous levels showed a trend similar to the three scenarios for a GCM, but the actual values varied. Based on average of GCMs (Fig.7),the increase in tops weight was smaller for RCP-6.0 scenario than for other scenarios for both 2025 and 2050 projections, with the values that varied by no more than 0.5 to 2.3% between three RCPs. For the 2025 projections, the tops weight for the cultivar MNH-886 showed an increase of 3.5 to 3.0% for RCP-8.5 and 6.0 at 57 kg P ha^{-1}, RCP-4.5 also showed the same result with high variation in projection of tops weight at the rate of 114 kg P ha^{-1}. For 2050 cultivar MNH-886 predicted high variation in all the scenarios and phosphorous levels. The projection by the model for FH-142 showed values larger than for MNH-886. Maximum variation was projected for 2050 by three RCPs under all phosphorous levels.

4. Discussion

Potential strategies were suggested for various scenarios that were analyzed in this study for cotton growth and yield in 2025 and 2050 for adoption by policy maker and farmers. As the study conducted by Moss et al. (2010) suggested, the use of multiple GCMs and greenhouse gas emission scenarios to represent the wide rages of conditions to minimize the uncertainties caused by GCMs and RCPs.

Negative effects of climate change can be minimized by prediction of proper planting dates (Carbone et al., 2003; Nasim et al., 2016b), and increase in precipitation for the period is also beneficial (IPCC, 2007). This study showed that the phosphorous level 57 kg ha^{-1}produced more increase in yield at harvest maturity than the other phosphorous levels with environmental modification of two GCMs (average) and three RCPs. Different phosphorous levels were used to reduce the negative impact of phosphorous (efficiency or deficiency) for cotton production for 2025 and 2050 projections. Yield at harvest maturity showed a decrease in cases where there was a projected increase in precipitation while tops weight increased as reported by Adhikaria et al., (2016). Part of the increase in yield was due to the increase in CO_2 concentration for both the 2025 and 2050 projections. For the 2025 projections, the RCP-8.5 that had higher CO_2 concentrations also generated a higher increase in the average grain yield compared to the other RCPs based on the selected GCMs Bao et al., (2015a) also conformed these results. The high percent change in yield was observed at 57 kg P $ha^{-1}$and 114 kg P ha^{-1} based on RCP-6.0and 4.5. The RCP-8.5 showed the lowest decrease in yield (0.7%) for 2025 from the base, which means that simulations of the GCMs were more stable in response to changes in the RCP-8.5. Yields of MNH-886cotton showed greater decrease under all three RCPs.

Among the three RCPs, the decrease in yield at harvest maturity (based on average of GCMs) was due to the increase in precipitation generated for the 2025 projections. However, the precipitation deficit projected by the average of the GCMs led to a decrease in yield for phosphorous levels. The simulation for yield at harvest maturity based on RCP-8.5 was more sensitive to change in yield compared to the two other RCPs. The phosphorous levels among scenarios and GCMs for

both the 2025 and 2050 projections decreased compared to the higher phosphorous levels, which means that the low phosphorous application can reduce the uncertainty associated with the GCMs and RCPs. This projection shows that use of control (0 kg P ha^{-1}) phosphorous is a promising adaptation strategy that predicted higher yield at harvest maturity and higher tops weight under all RCPs for both the 2025 and 2050 projections. Different cultivars showed different behavior in changing climate. The cultivar FH-142 showed a larger increase in yield at harvest maturity and tops weight than the other cultivars when57 and 114 kg P ha^{-1}were applied. Overall, yield was mainly affected by the changes in phosphorous levels, while the number of days from planting to maturity was mainly affected by the different RCPs due to different projections in temperature for 2025 and 2050.

5. Conclusion

From the present research study conclude that the number of days to maturity for cotton crop cultivars increased because of the projected increase in temperature for phosphorous levels, while yield increased due to the potential benefit from the projected increase in precipitation and CO_2 concentration. High phosphorous levels have a negative impact by climate pattern projected by average of GCMs. These results show the future climatic risks on cotton crop yield and also demonstrate the importance of crop simulation models and climate projection models for future sustainable food security. Nevertheless, as with any study, there are limitations inherent in the methodology and evaluation of research conducted at a single location (Tebaldi and Arblaster, 2014). Future studies should be conducted at additional/multiple locations using different cotton cultivars and various types of climate models to examine new potential strategies.

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